Forecast opportunities for European summer climate ensemble predictions using Self-Organising Maps

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ABSTRACT

Current state-of-the-art dynamical seasonal ensemble prediction systems (EPS) still show limited predictive skill, particularly over Europe in summer. We propose a neural network-based classification of individual ensemble members before performing a hindcast skill analysis. This classification targets high skill cases emerging from large-scale atmospheric regimes associated with the dominant modes of summertime low-frequency variability in the North Atlantic-European sector (NAE). This classification allows to then select those ensemble members that better predict the phase of the summer North Atlantic Oscillation (SNAO) and East Atlantic Pattern (EAP). Our baseline is a set of teleconnection patterns in NAE identified by Self-Organising Maps (SOM) using ERA-20C reanalysis data. We illustrate our methodology with an example with one set of hindcast ensemble simulations with 30-members generated by the MPI Earth System Model. We achieve better predictive skills at 3-4 months lead time for sea level pressure and geopotential height anomalies at 500 hPa.

CCS CONCEPTS

• **Applied computing** → **Environmental sciences.**

KEYWORDS

ensemble prediction, European climate, self-organising maps

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1 INTRODUCTION

Leading modes of atmospheric variability relevant for European summer climate are linked to the North Atlantic Jet (NAJ). In the North Atlantic-European sector (NAE), the NAJ modulates the occurrence and persistence of weather regimes and controls the location of storm tracks, thus acting as a key driver for temperature and precipitation extremes [3, 6]. Nevertheless, current state-of-the-art climate models strive in accurately representing NAJ variability and likely consequently show limited predictive skill for summer forecasts, particularly over Europe [2]. We present a neural network-based framework to circumvent such weak dynamical links in the model and achieve improved summer forecast skill.

Dynamical seasonal predictions are obtained by ensemble of simulations in Ensemble Prediction Systems (EPS), for which predictive skill is usually assessed by taking a mean over the whole set of ensemble members. Instead, recent works have shown that NAJ teleconnections can be used a priori to guide the selection of ensemble members that predict specific dynamical links to sources of high predictability, leading to improved skill [5]. For summer seasonal climate ensemble predictions in NAE, such identification of high skill cases has mainly focused on the Circumglobal Teleconnection Pattern [17]. While this teleconnection is related to the subtropical component of NAJ, predictability associated with the eddy-driven component of NAJ has been less explored in initialised ensemble predictions [16, 18].

Going beyond previous work, here we identify forecast opportunities for skillful European summer climate predictions using a neural network approach. We perform the analysis for an EPS based on the Max Planck Institute Earth System Model before assessing the hindcast skill. As a first step, we focus on predictability

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emerging from large-scale atmospheric regimes associated with the combined variability of both components of the NAJ.

2 METHOD

2.1 Indices

The summer North Atlantic Oscillation (SNAO) and East Atlantic Pattern (EAP) are the two main circulation indices often used as diagnostic tools to quantify changes in speed and location of NAJ [1, 7]. Together, SNAO and EAP define the dominant summer regimes in NAE. Traditionally, these indices are defined as the first two empirical orthogonal functions of NAE summer sea level pressure (SLP). Whilst SNAO is described by a meridional dipole in SLP between the Icelandic Low and Azores High, EAP has a more zonal dipole structure with pressure centres shifted south-eastwards compared to those of the SNAO. However, because EAP seems to modulate the surface expression of SNAO, both indices are necessary to describe NAJ variability [24]. Positive (negative) SNAO (EAP) phases correspond to anomalously northerly position of NAJ. In NAE these phases are associated with warmer and drier conditions in northern and central regions, and colder and wetter over south. Generally, negative (positive) SNAO (EAP) phases show a reverse pattern. As an alternative to this two-valued classification, we use a finer classification of NAE teleconnection patterns [12] to evaluate NAJ variability and to target windows of opportunity in an EPS.

2.2 Datasets

2.2.1 Reanalysis. We define our finer classification of teleconnection patterns as the dominant summer large-scale atmospheric regimes occurring throughout the 20th century in the NAE sector (70°W - 40°E , 25° - 80°N). For this purpose we use July and August monthly means SLP from ERA-20C reanalysis [19] covering the period of 1900-2010. The classification is obtained by the neural network classifier Self-Organising Maps (SOM).

2.2.2 Model output. Our second dataset is a set of 30-member hindcast simulations with the Max Planck Institute Earth System Model in its mixed-resolution setup (MPI-ESM-MR) covering the period 1902-2008. The atmospheric component ECHAM6 [21] has a resolution of T63L95, and the oceanic component MPI-OM [13] has a resolution of TP04L40. External forcing is taken from CMIP5 [8]. We use July and August monthly means (3-4 months lead time) of SLP, geopotential height at 500 hPa (Z500) and total precipitation from this hindcast.

An ensemble of 30-member 6-month long hindcasts is initialized in May every year from 1902-2008. Initial conditions for hindcasts are taken from an assimilation experiment. The assimilation experiment is performed using the MPI-ESM-MR with full-field nudging by Newtonian relaxation towards all atmospheric and ocean levels except in the boundary layer. The atmosphere conditions of vorticity, divergence, three-dimensional temperature and two-dimensional pressure are taken from ERA-20C. In the ocean, three-dimensional daily mean salinity and temperature anomalies are nudged at a relaxation time of approximately 10 days. The ocean state is derived in an ocean-only simulation performed with MPI-OM forced with the atmospheric variables from ERA-20C. The

three-dimensional atmospheric and ocean fields of the assimilation experiment form the initial conditions, and ensemble members are generated by small perturbations of the atmospheric state by disturbing the diffusion coefficient in the uppermost layer.

2.2.3 Preprocessing. At every gridpoint we compute anomalies by removing seasonal cycle and linear trend, in order to eliminate the centennial-scale climate change signal. We use July-August seasonal means (JA) to focus on the low-frequency dominant summer atmospheric regimes. In addition, all data have been weighted by the cosine of latitude to take into account the dependence of the gridpoint density on latitude. The final dataset used for training consist of 111 gridded SLP maps composed of 30×59 pixels at approximately 1.875° resolution.

2.3 Self-Organising Maps

We use JA SLP fields from ERA-20C reanalysis to train a Python implementation of Self-Organising Map (SOM) [22]. SOM is a non-linear method based on unsupervised learning with two-layer neural networks [14]. SOM's architecture allows for a reduced and ordered representation of high-dimensional datasets by a smaller set of variables. The SOM algorithm also provides a metric among those latent variables. This finer classification sets the basis for efficient application of SOM to explore large-scale, slow varying processes. Consequently, SOM has been successfully used for climate characterisation (e.g. [11, 20]).

In a typical two-layer SOM, the input layer corresponds to feature vectors $\mathbf{z}$ from dataset $\mathbf{D}$, while the output layer is the *SOM map*. The SOM map is a topological ordering of neurons usually in 2D grid (denoted SOM_{ij} , where i and j are the grid indices of the SOM map). This layer is fully connected to the input layer via weight vectors $\mathbf{w}$ with the same dimension as $\mathbf{z}$. The lattice structure of the layers permit to calculate a measure of distance (here Euclidean distance) and identify the shortest path between neurons of both layers, thereby assigning as Best Matching Unit the respective closest neuron in the SOM map, iteratively. A fundamental property of SOM is the topological ordering: neighbouring neurons SOM_{ij} represent similar neurons in the input data space and therefore share similar properties. Hereafter we adopt *mode* as terminology to refer to neurons in the SOM map, i.e. SOM_{ij} . For details on the SOM algorithm see [15].

In agreement with previous studies for the region, the classification is obtained on a 5×5 rectangular lattice of neurons. We choose training parameters as a compromise to keeping low quantisation and topological errors, while achieving a detailed view on the representative patterns associated with combined SNAO(+/-) and EAP(+/-) indices. We find that optimum parameters are *i*) initial spread of the neighbourhood function $\sigma(0) = 0.55$ (Gaussian) and *ii*) learning rate 0.4, for a maximum of 10000 iterations in batch training mode.

To facilitate interpretation of the SOM modes as corresponding to one of the four dominant summer regimes (see 2.1), we choose a Hierarchical Agglomerative Clustering algorithm using Ward dissimilarity to objectively cluster similar SOM modes as representative patterns for the dominant summer regimes ($k = 4$). [10]. Note that during learning, each observation in $\mathbf{D}$ is associated with only one mode SOM_{ij} in the trained SOM map. In other words, this

analysis assigns one dominant cluster per summer each year, i.e. a time series of the observed dominant summer regimes (C_{obs}).

2.4 Ensemble subsampling

We perform an ensemble subsampling with the aim of leveraging the MPI-EPS before calculating the ensemble mean and assessing the hindcast skill. This procedure assumes that retaining only ensemble members which predict the observed dominant summer regime (C_{obs}) will improve the forecast skill in MPI-EPS. We refer to this refinement as observed-mode strategy. We perform the following steps, per hindcast year (1902 - 2008):

- (1) project JA SLP mean of each n ensemble member Y_{ny} onto the SOM map
- (2) calculate RMSE between each pairs (Y_{ny}, SOM_{ij})
- (3) denote *winner* the SOM_{ij} for which RMSE is minimum (i.e. most similar mode)
- (4) verify to which cluster the *winner* mode belongs, i.e. C_{win}
- (5) retain Y_{ny} in the ensemble only if $C_{obs} = C_{win}$.

This procedure selects a subsample of potential skillful ensemble members per year. This selection of ensemble members is used to calculate the ensemble mean of SLP, Z500 and TP.

2.5 Seasonal hindcast skill analysis

The hindcast skill of MPI-EPS against the ERA-20C data is assessed using two skill scores. The first is point-wise detrended anomaly correlation coefficient (ACC) [4], which describes the model ability to reproduce the reference anomalies and have values in the range $[-1,1]$: the higher the score, the better. The second skill metric is the spread-error ratio [9], which measures the EPS reliability in representing the full uncertainty range as realistic as possible. Thus, the mean of the ensemble spread should be about equal to the RMSE over the same period (i.e. ideally equal one). An EPS is overdispersed (underdispersed) if the spread-error ratio is greater (smaller) than one, leading to unreliable forecasts if uncalibrated.

3 EVALUATION

We present results for a preliminary hindcast analysis with a set of 10 ensemble members. We first evaluate the model ability to predict the observed dominant summer regimes C_y . We find that regimes associated with a northerly position of NAJ and warmer/drier conditions in northern Europe (SNAO+ and EAP-) are more frequent from 70s onward (Fig. 1 top). This is in line with previous studies which suggest a poleward shift of NAJ in response to anthropogenic forcing (e.g. [16, 23]). Our results suggest that potential predictability in the model shows a marked variability, with about a third of MPI-EPS members predicting the observed dominant summer regime per year (Fig. 1 bottom). The model seems to strive the most in predicting years dominated by EAP, likely reflecting a poor representation of Circumglobal Teleconnection Pattern as in e.g. [2].

In Fig. 2 we show results of seasonal hindcast skill analysis of 3-4 months lead time SLP anomalies for the 1902 - 2008 period, focusing in a section of Europe (35°N - 70°N , 10°W - 30°E). Analysis for Z500 show overall similar results (not shown). We compare skill metrics for the full ensemble and the observed-mode strategy with selected members. With the full ensemble, we find very limited

Figure 1: Top: Low-frequency variability of the dominant clusters of summer regimes within each decade. For example, the first bar denotes years 1900-1909 and shows the percentage of years within this decade belonging to each cluster (colour coded). Bottom: Fraction of MPI-ESM-MR ensemble members that predict the observed dominant clusters of summer regimes.

predictive skill over Europe (Fig. 2 top-left), about 1% of agreement with ERA-20C (Fig. 2 top-right). One reason for the limited skill is the high overdispersion of ensemble members in most Europe (Fig. 2 bottom-left). Assuming that this overdispersion reflects the influence of different physical processes related to NAJ variability, we now target predictions with the observed-mode strategy to select ensemble members. We first compare the ensemble mean calculated with the full and selected members (Fig. 3 bottom). A consequence of the subsampling is the higher temporal variability of the selected ensemble mean, since the ensemble spread is reduced for every start date. We achieve better agreement with ERA-20C, as illustrated by the linear regression line of selected members being much closer to the line of perfect linear regression (grey line). We find significantly higher skill for JA SLP anomalies, particularly over the northern sector (Fig. 2 bottom), and improved spread-error-ratios of about 1 in many areas (Fig. 2 bottom-right). The mean ACC increases to about 40% agreement with ERA-20C (Fig. 3 top). Highest ACC improvement is found over regions of marked SNAO

influence. Lower improvement in the southern sector is probably due to influence of teleconnections not targeted in our analysis, such as Indian Monsoon (e.g. [6]). Our results are in line with a previous analysis of this set of simulations for Z500 using k-means clustering [16].

Figure 2: MPI-ESM-MR skill against ERA-20C for 3-4 mon lead time SLP anomalies for the 1902-2008 period. (top) ACC considering the full ensemble (left) and the selected ensemble for the European region (right). Stippling represents significance at the 95% confidence level. (bottom) Spread-error ratios for the full (left) and selected ensemble (right). White shading corresponds to ratio = 1 ± 0.05 .

4 CONCLUSIONS & FUTURE WORK

We show a methodology that combines dynamical ensemble predictions and selection of ensemble members by Self-Organising Maps to systematically find forecast opportunities for European summer climate skillful forecasts. By targeting the correct representation of the two dominant modes of summertime North Atlantic Jet variability in the ensemble prediction system, we better evaluate the model performance. Our subsampling approach leverages the EPS ensemble mean, achieving improved skill scores for May predictions of July-August SLP and Z500.

Our ongoing analyses build on recent studies that link the large-scale atmospheric regimes investigated here with tropical [17] and subtropical [18] spring sea surface temperatures in the North Atlantic. We currently perform a flow-dependent hindcast skill verification based on spring sea surface temperature patterns preceding these atmospheric summer regimes. This analysis is crucial to verify the potential of performing an ensemble selection before initialisation.

Figure 3: (top) Comparison between ERA20C (grey line) and the ensemble mean over the full ensemble (blue line) and the selected ensemble (red line) from MPI-ESM in 1902-2008 for the region $35^{\circ}\text{N} - 70^{\circ}\text{N}$, $10^{\circ}\text{W} - 30^{\circ}\text{E}$. Grey circles indicate the value of each ensemble member. Time series are smoothed with a 3-month running mean. (bottom) Scatter-plots of ERA20C compared to the ensemble mean of MPI-ESM in 1902-2008 over the full (orange circles) or the selected ensemble (blue circles) including linear regression.

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